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ORIGINAL PAPER

# The prediction of lean meat and subcutaneous fat with skin content in pork cuts on the carcass meatness and weight

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**Abstract**
Early *post-mortem*, objective and non-destructive prediction of tissue distribution in the major pork cuts is a challenge for the meat industry. Mathematical models to predict pig carcass composition using total lean meat percentage and carcass weight were evaluated in this study. The data were obtained from 455 cold pig carcasses which were dissected according to the EU reference method; total lean meat percentage and carcass weight ranged from 42.45 to 69.21% and from 23.26 to 55.22 kg, respectively. Developed empirical models gave a reasonable fit to the experimental data and successfully predicted the carcass composition and tissue distribution in primal cuts. The second order polynomial models showed high coefficients of determination for prediction of experimental results (between 0.612 and 0.929), while the artificial neural network (ANN) model, based on the Broyden–Fletcher–Goldfarb–Shanno iterative algorithm, showed better prediction capabilities (overall $r^2$ was 0.889). The newly developed software, based on ANN model is easy, fast, cheap and with sufficient precision for application in the meat industry.

**Keywords** Pig · Carcass composition · Tissue distribution · Meatiness · Fatness · Mathematical modelling

## Introduction

The grading of pig carcasses according lean meat as percentage of carcass weight (SEUROP system: class S ≥ 60; 55 ≤ class E < 60; 50 ≤ class U < 55; 45 ≤ class R < 50; 40 ≤ class O < 45; class P < 40) has been obligatorily performed in the EU since 1985 [1, 2]. The pig carcasses are graded according to the lean meat percentage, which is evaluated on-line indirectly via measurement of predicted variables. Pig carcass grading is based on the objective on-line measurements of carcass characteristics (backfat and/or *longissimus* muscle thickness) on the slaughter line using various methods and/or instruments (from measurement obtained with a ruler to measurement obtained with an AUTOFOM—Fully Automatic Ultrasonic Device) previously calibrated to predict lean meat percentage. The protocol and rules for the calibration of the pig carcass classification methods and/or instruments were summarised in an EU regulation from 2008 [3].

The calibration of pig carcass grading methods and/or instruments involve the total or partial (EU reference dissection method) manual dissection by the knife of at least 120 one-half carcasses. According to the EU reference dissection method, only the four major cuts of the carcass are fully dissected; this means the complete tissue separation of ham, loin, shoulder and belly into muscle, bone and fat. Fat is divided into subcutaneous fat, including skin and intermuscular fat. The weight of the lean in the four major cuts together with tenderloin is calculated by subtracting the total of the non-lean elements of the four cuts from the total weight of the cuts before dissection. Dissection largely destroys the financial value of the carcass and also requires expensive laboratory facilities and staff, but comparing

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to total dissection, EU reference dissection is simplified method with reduced dissection costs and time. Several types of errors may occur during the slaughter, dressing, splitting, sampling, cutting, dissection and weighting processes, which may influence the accuracy of the equation for estimation of lean meat percentage. Grading methods shall be authorized only if the root mean squared error of prediction (RMSEP), computed by a full cross-validation technique, is less than 2.5 [3–5].

Currently, most slaughterhouses utilise the following systems/methods/instruments for EU on-line pig carcass classification: ZP method (Zwei-Punkt-Messverfahren), Intrascope (Optical Probe), Fat-O-Meat'er (FOM), Hennessey Grading Probe (HGP), Ultrasonic Pig Carcass Grading (UltraFom), CSB Ultra-Meater (UM), Fully Automatic Ultrasonic Carcass Grading (AUTOFOM), which are authorized by the Commission in EU [6–8]. In Serbia, FOM is the most commonly used method, which measures the difference in light reflectance as it passes through fat and muscle tissue and records the thickness of each tissue. All of these systems, except the AUTOFOM III device, provide information only about backfat and *longissimus* muscle thickness, i.e. about total lean meat percentage and grading class (SEUROP) together with the total carcass weight, without any additional information about carcass composition and tissue distribution, i.e. about the lean meat percentage of the primal cuts, their total weight and/or the weight of lean meat for each cut. However, the meat industry is very interested in early *post-mortem* and easy prediction of carcass composition and tissue distribution in the major cuts in order to optimise their commercial cutting and further fabrication. Several studies were conducted to evaluate methods to predict cut composition and tissue distribution in whole pig carcasses, using direct measurements taken in vivo or on the slaughterline.

In the study performed by Gresham et al. [9], the live animal and carcass data were collected and a predictive model for the estimation of carcass composition was developed, according to live animals data and carcass ultrasonic measurements.

Another approach using dual-energy X-ray absorptiometry (DXA) was evaluated as a method for measuring body composition of pigs [10]. DXA was used on carcasses to estimate fat, lean, bone mineral content and total tissue masses of the major primal cuts and overall carcasses [11–14]. The DXA estimations were compared and used to predict the dissected lean, fat (including skin), bone and weight of primal cuts and carcasses, as well as to predict the Canadian and the European lean yields [11].

The magnetic resonance imaging (MRI), which was used as a diagnostic tool for human medicine was used for carcass composition [15]. MRI technique generates cross-sectional images of all parts of the body with a high contrast between soft tissues, and it was used as an in vivo technique for the determination of body composition [16–19]. The determination of the tissue composition of pig carcasses and cuts was also performed by MRI technique in the study of Monziols et al. [20, 21]. Pig carcasses were cut into the four primary cuts that were analyzed with a low field MRI imager before a total dissection. Images were then processed to identify and quantify pixels representing muscle, subcutaneous fat and intermuscular fat fractions. MRI provided a good prediction of muscle content in cuts and carcasses, with $r^2$ ranging from 0.970 to 0.997.

The electromagnetic scans were also used for the estimation of carcass composition [22].

Different approach for determination of body composition was observed in the investigation by Swensen et al. [23, 24] in which the carcass composition was determined using physical dissection and chemical analyses of soft tissue. Using dissectable components, high ($r > 0.85$) correlations occurred between percentage of fat-free lean and percentage of lipid, percentage of dissectable fat, and lipid in the whole-side grind; between weights of dissectable lean and fat-free lean; and between weights of lipid in the whole-side grind and lipid, dissectable fat, and dissectible lean.

FOM grading probe was used in the investigation of Gispert et al. [25] for the calculation of FOM backfat and loin depth the percentage lean of the ham, as a new predictor.

According to the study of Schinckel et al. [26] carcass data and live measurements were used to evaluate the carcass composition according to the magnitude of ractopamine (RAC) treatment. Prediction equations from live or carcass measurements predicted the lean mass of the pigs and the lean mass of the pigs. The video image analysis system was used to predict pork carcass composition [27]. Pork carcasses were selected from a commercial packing plant to differ in weight, FOM predicted percentage lean and gender.

The classification or carcass quality evaluation in bovine carcasses was studied in many studies [28–30]. Within these investigations, the main principle of grading the meat quality is based on the visual concept, obtained by the classifier, which indicates the lean quantity. Within these studies, the main goal was to predict carcass lean meat content using the classifier [22, 30, 31] or using the automated grading [32].

The objective of the study performed by Čítek et al. [33] was to identify the pig belly characteristics and to develop regression equations predicting its composition. According to video image and chemical analysis, they successfully predicted pig belly fat content. In the studies by Johnson et al. [34] various regression formulas were developed to predict the decimal fraction of protein and the percentage of fat, using either the carcass data, specific gravity ham measurements, loin section measurements or various combinations of these. In prediction equation, specific gravity of the carcass accounted for 73.4% of the variation found in percentage of protein, while

the prediction of fat percentage reached the 72.0% limit of variation.

The studies using ANN are rare [22], because the nowadays carcass classification methods are based mostly on objective measurements, which are found to be strongly correlated to lean meat content, and therefore the use of standard regression methods could be the adequate mathematical tool. The investigations regarding carcass classification were developed mainly on back propagation ANN calculation [35, 36], with the exception of a few studies involving the radial basis function networks (RBF) [37] or learning vector quantization [38]. ANN showed its best potential with some advantages over the conventional regression methods, showing to be more accurate, especially in case of non-linear relations between input and output variables.

The objective of this work was to study the possibility of predicting the distribution of tissues (lean meat and subcutaneous fat with skin) in the primal cuts (ham, loin, shoulder and belly) as a function of total lean meat percentage of carcass, grading class (SEUROP) and total carcass weight, based on the EU dissection method as a reference method for estimating the lean meat percentage of pig carcasses. Second order polynomial (SOP) models and artificial neural network (ANN) model were used for mathematical modelling.

## Materials and methods

### Data collection

The study was carried out on 455 carcasses obtained from castrated male and female purebred pigs (Large White, Landrace, Duroc, Hampshire and Pietrain) and from their two-, three- and four-breed cross pigs from 17 industrial pig farms. All the pigs were slaughtered in the four largest Serbian commercial slaughterhouses according to routine procedures.

After chilling (24 h *post-mortem*), standard carcass presentation was performed [39], and the left side of each carcass was divided into 12 cuts. The four main parts (ham, loin, shoulder and belly) were dissected into muscle, subcutaneous fat with skin, intermuscular fat and bone, according to the approved EU reference method [5]. The total lean meat percentage was calculated using the formula according to EU regulation from 2008 [3]. All weights were recorded to the nearest 5 g. The cutting was performed always by the same trained technicians. The number of butchers in the dissection team varied between 4 and 7.

### Statistical analysis

The collected data were presented using descriptive statistics tables. The analysis and mathematical modelling was performed using STATISTICA 10.0 [40].

### SOP models

According to general recommendations, prior to artificial neural network (ANN) modelling, eight SOP models were developed. SOP models were used for the modelling, rather than first order polynomials, due to the complexity of the data and the pronounced nonlinear dependence between variables. Furthermore, ANOVA was performed, in order to explore the effects of the input variables over the outputs, as well as to justify the later use of the ANN model by the coefficient of determination ($r^2$).

The SOP model was used for estimation of the main effect of the process variables on responses. The variables used for modelling were TLMP (total lean meat percentage), grading Class (SEUROP) and TCCW (total cold carcass weight). The modelling variables were relatively easy to obtain in the commercial slaughterhouses using the standard measuring equipment (weighing scale for TCCW, instruments for TLMP, and SEUROP system procedure for grading Class). The correlation analysis showed that some of these variables were not independent (correlation coefficient between TCCW and Class was −0.288; between TCCW and TLMP −0.304; and between Class and TLMP 0.930, statistically significant at $p < 0.01$ level), but all proposed variables were used for further statistical analysis in order to improve the behaviour of SOP and ANN models. The observed response variables were: HLMP (ham lean meat percentage), HSFSP (ham subcutaneous fat with skin percentage), LLMP (loin lean meat percentage), LSFSP (loin subcutaneous fat with skin percentage), SLMP (shoulder lean meat percentage), SSFSP (shoulder subcutaneous fat with skin percentage), BLMP (belly lean meat percentage) and BSFSP (belly subcutaneous fat with skin percentage). The SOP model was fitted to data collected from experimental measurements [41, 42]:

$$Y_k = \beta_0 + \sum_{i=1}^{3} \beta_i X_i + \sum_{i=1}^{3} \beta_{ii} X_i^2 + \sum_{i=1}^{2} \sum_{j=2}^{3} \beta_{ij} X_i \cdot X_j, k = 1 - 8 \quad (1)$$

where: $\beta_0$, $\beta_i$, $\beta_{ii}$, $\beta_{ij}$, are constant regression coefficients for intercept, linear, quadratic and product term, respectively, $Y_k$ is the response variable, while $X_i$ and $X_j$ are independent variables. The significant terms in the model were found using ANOVA for each dependent variable.

### ANN modelling

A multi-layer perceptron model (MLP), which consisted of three layers (input, hidden and output) was used for model establishment. This model has been proven as quite capable of approximating nonlinear functions

[43, 44]. Before the calculation, both input and output data were normalised in order to improve the behaviour of the ANN. During this iterative process, input data were repeatedly presented to the network [45, 46]. Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm was used as an iterative method for solving unconstrained nonlinear optimization problems in ANN modelling.

The experimental database for ANN was randomly divided into: training, cross-validation and testing data (with 60, 20 and 20% of experimental data, respectively). The training data set was used for the learning cycle of ANN and also for evaluation of the optimal number of neurons in the hidden layer and the weight coefficient of each neuron in the network. It was assumed that successful training was achieved when learning and cross-validation curves approached zero.

Coefficients associated with the hidden layer (weights and biases) were grouped in matrices $W_1$ and $B_1$. Similarly, coefficients associated with the output layer were grouped in matrices $W_2$ and $B_2$. It is possible to represent the neural network by using matrix notation ($Y$ is the matrix of the output variables, $f_1$ and $f_2$ are transfer functions in the hidden and output layers, respectively, and $X$ is the matrix of input variables) [47]:

$$Y = f_1(W_2 \cdot f_2(W_1 \cdot X + B_1) + B_2) \tag{2}$$

Weights (elements of matrices $W_1$ and $W_2$) were determined during the ANN learning cycle, which updated them using optimisation procedures to minimise the error between network and experimental outputs [46, 48], according to the sum of squares ($SOS$) and BFGS algorithm, used to speed up and stabilise convergence [8]. The coefficients of determination were used as parameters to check the performance of the obtained ANN model.

### Sensitivity analysis

Sensitivity analysis is a widely accepted technique used in decision theory for exploring the effects of the uncertainties in the observed parameters of a developed model [49]. Neural networks can perform an approximation to experimental results, which could be partially noisy and/or contain partially imprecise data, so sensitivity analysis is necessary to check if the neural network could behave erroneously [50]. On the basis of the developed ANN model, sensitivity analysis was performed in this work in order to more precisely check the influence of input variables on the observed outputs. Infinitesimal amounts (+0.0001%) were added to each input variable, in 10 equally spaced individual points encompassed by the minimum and maximum of the training data.

### The accuracy of the models

The numerical verification of the developed models was tested using coefficient of determination ($r^2$), reduced Chi square ($\chi^2$), mean bias error (MBE), root mean square error (RMSE) and mean percentage error (MPE). These commonly used parameters can be calculated as follows [51]:

$$\chi^2 = \frac{\sum_{i=1}^{N}(x_{\exp,i} - x_{pre,i})^2}{N-n}, RMSE = \left[\frac{1}{N}\cdot\sum_{i=1}^{N}(x_{pre,i} - x_{\exp,i})^2\right]^{1/2},$$
$$MBE = \frac{1}{N}\cdot\sum_{i=1}^{N}(x_{pre,i} - x_{\exp,i}), MPE = \frac{100}{N}\cdot\sum_{i=1}^{N}\left(\frac{\left|x_{pre,i} - x_{\exp,i}\right|}{x_{\exp,i}}\right) \tag{3}$$

where $x_{exp,i}$ stands for the experimental values and $x_{pre,i}$ are the predicted values calculated by the model for these measurements. $N$ and $n$ are the number of observations and constants, respectively.

## Results and discussion

Some summary statistics of the dissected carcasses are presented in Table 1. The number of carcasses in the grading Classes R, U, E and S were 22 (4.8%), 70 (15.4%), 184 (40.4%) and 179 (39.3%), respectively.

The positive and highly significant correlations between HLMP, LLMP, SLMP and BLMP, as well as between HLFSP, LLFSP, SLFSP and BLFSP are shown in Table 2. Also, negative, highly significant correlations between lean meat percentage tissues and subcutaneous fat with skin tissues were obtained (Table 2).

### SOP models and ANOVA

ANOVA was conducted for the obtained SOP models, and output variables were tested against the impact of input variables (Table 3). ANOVA analysis revealed that the linear term of TLMP considerably influenced the SOP model predictions of HLMP, HSFSP, LLMP, LSFSP, SLMP, SSFSP, BLMP and BSFSP calculation, and were statistically significant at $p < 0.01$ level.

The influence of the Class variable on the observed responses was generally low, but its impact could be observed in the nonlinear terms. The statistically significant influence of the nonlinear terms Class × TCCW ($p < 0.01$ level) and TLMP × TCCW ($p < 0.05$ level) were

**Table 1** Descriptive statistics of the 455 pork dissected carcasses

| | Input variables | | | Response variables | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | TLMP (%) | TLMC (kg) | TCCW (kg) | HLMP (%) | HSFSP (%) | LLMP (%) | LSFSP (%) | SLMP (%) | SSFSP (%) | BLMP (%) | BSFSP (%) |
| Average | 58.35 | 22.18 | 38.14 | 70.09 | 18.68 | 60.67 | 21.45 | 66.15 | 18.67 | 56.42 | 24.76 |
| SD | 4.48 | 2.77 | 4.48 | 4.69 | 5.12 | 5.97 | 5.97 | 4.27 | 4.27 | 7.04 | 6.19 |
| Min | 42.45 | 13.80 | 23.26 | 53.37 | 6.10 | 39.33 | 6.85 | 51.30 | 8.07 | 34.61 | 12.30 |
| Max | 69.21 | 31.85 | 55.52 | 81.75 | 34.59 | 76.47 | 41.68 | 77.05 | 31.11 | 73.77 | 45.55 |
| Skewness | −0.569 | −0.239 | −0.137 | −0.584 | 0.651 | −0.467 | 0.624 | −0.264 | 0.504 | −0.389 | 0.652 |
| Kurtosis | 0.306 | 0.128 | 1.581 | 0.193 | 0.102 | 0.310 | 0.303 | 0.294 | 0.051 | −0.206 | 0.161 |

*TLMP* total lean meat percent, *TLMC* total lean meat content, *TCCW* total cold carcass weight, *HLMP* ham lean meat percentage, *HSFSP* ham subcutaneous fat with skin percentage, *LLMP* loin lean meat percentage, *LSFSP* loin subcutaneous fat with skin percentage, *SLMP* shoulder lean meat percentage, *SSFSP* shoulder subcutaneous fat with skin percentage, *BLMP* belly lean meat percentage, *BSFSP* belly subcutaneous fat with skin percentage

observed for LSFSP calculation. According to ANOVA results, the influence of the linear term of TCCW was very influential for the prediction of HLMP and LSFSP, statistically significant at $p < 0.05$ level.

The coefficient of determination ($r^2$) for SOP models were rather good (0.612–0.929) (Table 3). According to results presented in Table 3, the higher $r^2$ values were attributed to SOP models in which the nonlinear terms had less effect and the linear term of TLMP was more pronounced. The relatively inaccurate results of the SOP models indicate that some other model (ANN model, for instance) would improve the validity of the model predictions.

The quality of the model fit was tested in Table 3, with the higher $r^2$ values, and the lower $\chi^2$, MBE, RMSE and MPE values showing the better fit to the experimental results [51]. Residual analysis of the developed model was also performed. Skewness measures the deviation of the distribution from normal symmetry. If the skewness is clearly different from zero, then the distribution is asymmetrical, while normal distributions are perfectly symmetrical. Kurtosis measures the "peakedness" of a distribution. If the Kurtosis is clearly different than zero, then the distribution is either flatter or more peaked than normal; the Kurtosis of the normal distribution is zero. The average and the standard deviation (SD) were also analysed and are shown in Table 3.

The residual analysis showed that the mean of residuals were equal to zero, and the standard deviation was between 1.245 and 3.841. These results showed a good approximation to a normal distribution around zero with a probability of 95% (2×SD), which means the developed SOP model had a good generalization ability to predict pig carcass composition for the range of observed experimental data.

## ANN model

The acquired optimal neural network model showed a good generalization capability for the experimental data, and could be used to accurately predict percentages of fat and meat in pig carcasses from a broad range of input parameters. According to ANN performance, the optimal number of neurons in the hidden layer for HLMP, HSFSP, LLMP, LSFSP, SLMP, SSFSP, BLMP and BSFSP calculation was 5 (network MLP 3-5-8) to obtain high values of $r^2$ (overall 0.889 for ANN during the training period, compared to 0.612–0.929 for SOP models) and low values of *SOS* (Table 4).

The goodness of fit between experimental measurements and model-calculated outputs, represented as ANN performance (sum of $r^2$ between measured and calculated HLMP, HSFSP, LLMP, LSFSP, SLMP, SSFSP, BLMP and BSFSP), during training, testing and validation steps, are shown in Table 5.

**Table 2** Correlation matrix of the response variables

| | HSFSP | HLMP | LSFSP | LLMP | SSFSP | SLMP | BSFSP |
|---|---|---|---|---|---|---|---|
| HLMP | −0.954 | | | | | | |
| LSFSP | 0.883 | −0.891 | | | | | |
| LLMP | −0.764 | 0.846 | −0.914 | | | | |
| SSFSP | 0.859 | −0.854 | 0.821 | −0.741 | | | |
| SLMP | −0.670 | 0.772 | −0.761 | 0.786 | −0.824 | | |
| BSFSP | 0.798 | −0.754 | 0.719 | −0.607 | 0.768 | −0.566 | |
| BLMP | −0.862 | 0.850 | −0.837 | 0.753 | −0.812 | 0.681 | −0.898 |

All correlations presented in this table are statistically significant at $p < 0.01$ level

*HSFSP* ham subcutaneous fat with skin percentage, *HLMP* ham lean meat percentage, *LSFSP* loin subcutaneous fat with skin percentage, *LLMP* loin lean meat percentage, *SSFSP* shoulder subcutaneous fat with skin percentage, *SLMP* shoulder lean meat percentage, *BSFSP* belly subcutaneous fat with skin percentage, *BLMP* belly lean meat percentage

**Table 3** ANOVA calculation partial dissected carcass variables (sum of squares are presented)

| | df | HLMP | HSFSP | LLMP | LSFSP | SLMP | SSFSP | BLMP | BSFSP |
|---|---|---|---|---|---|---|---|---|---|
| TLMP | 1 | 579.480+ | 599.294+ | 776.180+ | 782.888+ | 447.952+ | 428.353+ | 1055.377+ | 864.310+ |
| TLMP$^2$ | 1 | 0.053 | 1.000 | 0.824 | 2.488 | 1.437 | 4.268 | 1.259 | 21.128 |
| Class | 1 | 0.118 | 0.160 | 2.721 | 5.492 | 4.073 | 0.949 | 1.710 | 3.954 |
| Class$^2$ | 1 | 0.184 | 2.731 | 3.322 | 0.714 | 0.848 | 7.316 | 0.094 | 26.138 |
| TCCW | 1 | 7.962** | 8.903 | 7.306 | 25.936** | 1.914 | 7.452 | 2.653 | 57.176** |
| TCCW$^2$ | 1 | 0.028 | 15.257** | 9.022 | 1.036 | 0.019 | 14.217** | 0.703 | 16.977 |
| TLMP × Class | 1 | 0.199 | 3.007 | 1.976 | 2.162 | 0.648 | 5.731 | 0.602 | 30.742 |
| TLMP × TCCW | 1 | 0.001 | 0.922 | 18.255** | 23.881** | 4.283 | 0.110 | 10.957 | 2.647 |
| Class × TCCW | 1 | 1.504 | 13.332** | 8.957 | 33.037* | 12.925** | 1.750 | 8.324 | 0.193 |
| Error | 444 | 702.603 | 1829.967 | 2140.626 | 1869.821 | 2030.718 | 1793.038 | 4415.639 | 6682.284 |
| $\chi^2$ | | 1.558 | 4.058 | 4.746 | 4.146 | 4.503 | 3.976 | 9.791 | 14.817 |
| SD | | 4.51 | 4.62 | 5.45 | 5.69 | 3.64 | 3.73 | 6.38 | 4.82 |
| RMSE | | 1.244 | 2.008 | 2.171 | 2.029 | 2.115 | 1.987 | 3.119 | 3.836 |
| MBE | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| MPE | | 1.376 | 9.062 | 2.915 | 7.940 | 2.650 | 8.760 | 4.628 | 13.322 |
| $r^2$ | | 0.929 | 0.841 | 0.863 | 0.887 | 0.748 | 0.778 | 0.807 | 0.612 |
| Residual analysis | | | | | | | | | |
| Skewness | | 0.087 | −0.102 | 0.183 | −0.082 | −0.141 | 0.058 | −0.188 | −0.079 |
| Kurtosis | | 1.249 | −0.192 | −0.126 | 0.106 | −0.415 | 0.217 | −0.511 | 0.053 |
| Average | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| SD | | 1.245 | 2.010 | 2.174 | 2.032 | 2.117 | 1.990 | 3.122 | 3.841 |

Class—SEUROP

*TLMP* total lean meat percent, *TCCW* total cold carcass weight, *HLMP* ham lean meat percentage, *HSFSP* ham subcutaneous fat with skin percentage, *LLMP* loin lean meat percentage, *LSFSP* loin subcutaneous fat with skin percentage, *SLMP* shoulder lean meat percentage, *SSFSP* shoulder subcutaneous fat with skin percentage, *BLMP* belly lean meat percentage, *BSFSP* belly subcutaneous fat with skin percentage, $\chi^2$ reduced Chi square, *RMSE* root mean square error, *MBE* mean bias error, *MPE* mean percentage error, $r^2$ coefficient of determination

+Statistically significant at $p < 0.01$ level

*Statistically significant at $p < 0.05$ level

**Statistically significant at $p < 0.10$ level

The ANN model predicted experimental variables (HLMP, HSFSP, LLMP, LSFSP, SLMP, SSFSP, BLMP and BSFSP) reasonably well for a broad range of the process variables (as seen in Fig. 1, where the experimentally measured and ANN model predicted values of HLMP, HSFSP, LLMP, LSFSP, SLMP, SSFSP, BLMP and BSFSP are presented).

The accuracy of the ANN model could be visually assessed by the dispersion of points from the diagonal line in the graphics presented in Fig. 1. For the ANN model,

**Table 4** Artificial neural network model summary (performance and errors), for training, testing and validation cycles

| Network name | Training performance | Test performance | Validation performance | Training error | Test error | Validation error | Training algorithm | Error function | Hidden activation | Output activation |
|---|---|---|---|---|---|---|---|---|---|---|
| MLP 3-5-8 | 0.889 | 0.914 | 0.904 | 0.029 | 0.026 | 0.029 | BFGS 121 | *SOS* | Logistic | Identity |

Performance term represent the coefficients of determination, while error terms indicate a lack of data for the ANN model

the predicted values were very close to the measured values in most cases, in terms of $r^2$ values (shown in Fig. 1). *SOS* obtained with ANN model were of the same order of magnitude as experimental errors for HLMP, HSFSP, LLMP, LSFSP, SLMP, SSFSP, BLMP and BSFSP reported in the literature [46, 52].

The ANN model is complex (68 weights-biases) because of the high nonlinearity of the developed system [46, 53]. The $r^2$ values between experimental measurements and ANN model outputs, HLMP, HSFSP, LLMP, LSFSP, SLMP, SSFSP, BLMP and BSFSP were: 0.928, 0.843, 0.861, 0.885, 0.748, 0.774, 0.806 and 0.616, respectively, during the training period.

Table 6 presents the elements of matrix $W_1$ and vector $B_1$ (presented in the bias column), and Table 7 presents the elements of matrix $W_2$ and vector $B_2$ (bias) for the hidden layer, used for calculation in Eq. 2.

The quality of the model fit was tested and the residual analysis of the developed model was presented in Table 8. The ANN model had an insignificant lack of fit tests, which means the model satisfactorily predicted the pig carcass compositions. A high $r^2$ is indicative that the variation was accounted for and that the data fitted the proposed model satisfactorily [54, 55].

## Sensitivity analysis

In this study, the influence of the input variables at a specific position in the input space, over the output variables, were tested by sensitivity analysis. This indicates how sensitive the response variable calculated is to the observed domain of input variables. Sensitivity values are actual first-order derivatives evaluated at specific centile points for each input variable. For each input, the derivative is taken with respect to the target at ten evenly spaced locations with the observed minimum and maximum values. The exact values are calculated by the Taylor formula [56]. The influence of the input over the output variables, i.e. calculated changes of output variables for infinitesimal changes in input variables, as well as the importance of an input variable at a given point in the input space are shown in Fig. 2. The obtained values corresponded to the level of experimental errors, and also showed the TLMP, Class and TCCW influenced HLMP, HSFSP, LLMP, LSFSP, SLMP, SSFSP, BLMP and BSFSP.

As can be seen in Fig. 2, HSFSP, LSFSP, SSFSP and BSFSP were negatively affected by the infinitesimal changes in TLMP at the average values of the input space (close to the value of 58%, or 22 kg, according to Table 1). HLMP value increased at the centre of the input space for TLMP variable, while the values of LLMP, SLMP and BLMP were mostly positively affected by the changes in TLMP at the higher levels of the input space (closer to 69%, or more than 31 kg, according to Table 1). According

**Table 5** Coefficients of determination ($r^2$) between experimentally measured and ANN outputs, during training, testing and validation steps

| Cycle | HLMP | HSFSP | LLMP | LSFSP | SLMP | SSFSP | BLMP | BSFSP |
|---|---|---|---|---|---|---|---|---|
| Train | 0.963 | 0.914 | 0.926 | 0.935 | 0.857 | 0.868 | 0.894 | 0.753 |
| Test | 0.968 | 0.937 | 0.923 | 0.945 | 0.872 | 0.915 | 0.908 | 0.844 |
| Valid | 0.963 | 0.912 | 0.940 | 0.953 | 0.878 | 0.877 | 0.903 | 0.810 |

*HLMP* ham lean meat percentage, *HSFSP* ham subcutaneous fat with skin percentage, *LLMP* loin lean meat percentage, *LSFSP* loin subcutaneous fat with skin percentage, *SLMP* shoulder lean meat percentage, *SSFSP* shoulder subcutaneous fat with skin percentage, *BLMP* belly lean meat percentage, *BSFSP* belly subcutaneous fat with skin percentage

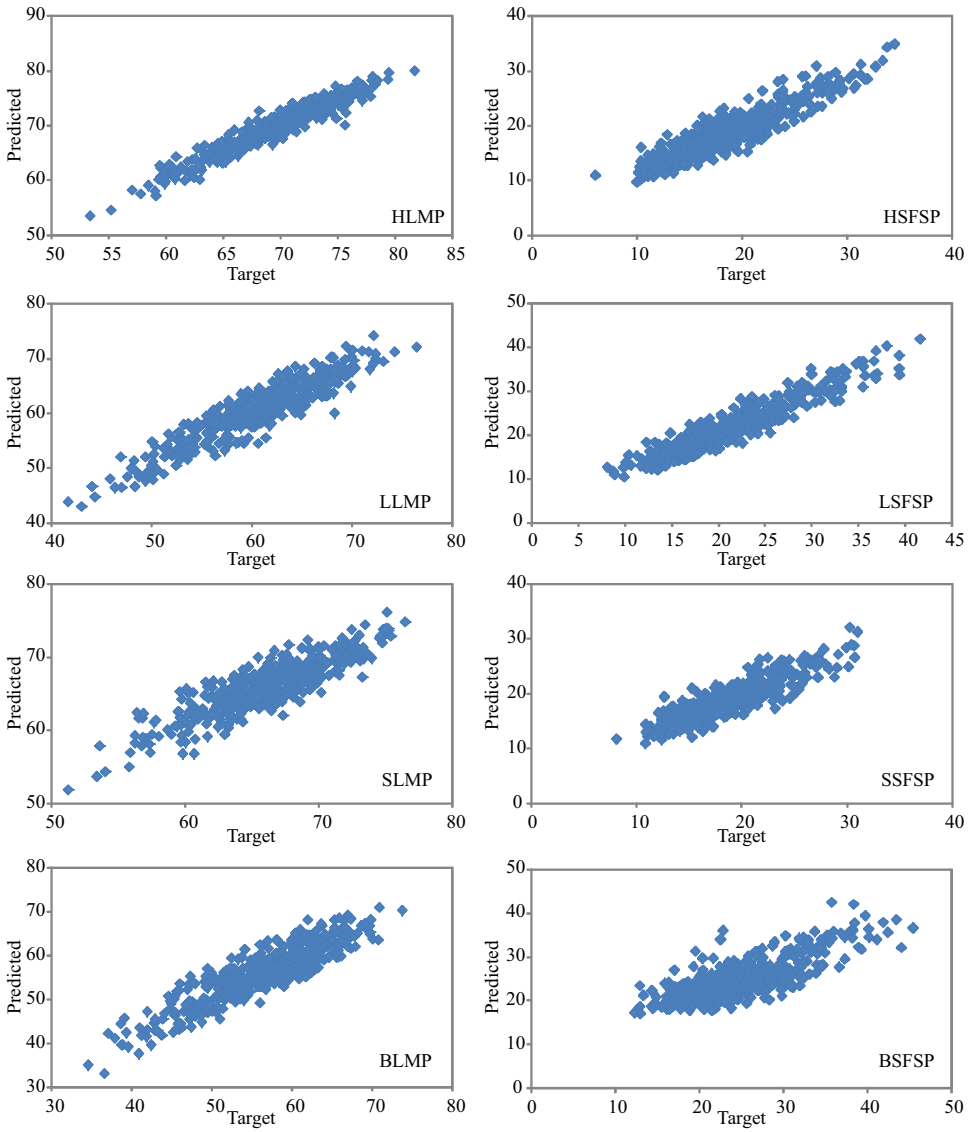


**Fig. 1** Partially dissected carcass variables and the ANN model predicted values of HLMP, HSFSP, LLMP, LSFSP, SLMP, SSFSP, BLMP and BSFSP

to results presented in Table 3 and Fig. 2, higher $r^2$ values were calculated for the ANN model as applied to different predictions of pig carcass composition, in which the effect of TLMP was more influential than other input variables. This finding was fully confirmed with by the results of the SOP model.

## Conclusion

The results of this study indicate that carcass total lean meat content in association with total cold carcass weight could be used for prediction of carcass composition and

**Table 6** Elements of matrix $W_1$ and vector $B_1$ (presented in the bias column)

| | TLMP | Class | TCCW | Bias |
|---|---|---|---|---|
| 1 | − 1.874 | 0.268 | 0.485 | − 2.183 |
| 2 | 0.378 | 0.305 | 0.804 | 0.191 |
| 3 | 1.044 | 5.055 | − 1.264 | 1.683 |
| 4 | − 1.327 | 0.914 | − 2.462 | − 1.165 |
| 5 | 1.248 | − 1.074 | 1.260 | 0.764 |

*TLMP* total lean meat percent, *TCCW* total cold carcass weight

tissue distribution in primal cuts. The second order polynomial models showed good prediction capabilities (the coefficients of determination for the observed variables were between 0.612 and 0.929), while the artificial neural network model, showed to be more adequate for the prediction of carcass composition and tissue distribution in primal cuts (overall coefficients of determination was 0.889). The ANN model (network MLP 3-5-8) exhibited the good fit to experimental results, and its results were applied for calculative software development. The newly developed software is easy, fast, cheap and with sufficient precision for application in the meat industry. The sensitivity analysis, which is calculated based on the ANN results, showed the influence of the lean meat percentage, SEUROP and total cold carcass weight on the percentage of: ham lean meat, ham subcutaneous fat with skin, loin lean meat, loin subcutaneous fat with skin, shoulder lean meat, shoulder subcutaneous fat with skin, belly lean meat and belly subcutaneous fat with skin. Beside these mathematical models, additional models with similar accuracy and objectivity could be developed using the same variables expressed in weight (kg).

**Table 7** Elements of matrix $W_2$ and vector $B_2$ (presented in the bias column)

| | 1 | 2 | 3 | 4 | 5 | Bias |
|---|---|---|---|---|---|---|
| HLMP | 1.785 | 1.026 | − 1.442 | − 0.800 | − 1.001 | 0.610 |
| HSFSP | − 0.689 | 1.103 | 1.193 | − 1.646 | 0.371 | 0.308 |
| LLMP | − 1.645 | 0.677 | 0.572 | − 1.872 | − 0.147 | 0.299 |
| LSFSP | 0.737 | − 0.010 | 0.127 | − 1.451 | − 0.430 | 0.742 |
| SLMP | 0.139 | − 1.006 | 2.680 | 2.641 | − 1.311 | 0.569 |
| SSFSP | − 0.613 | 1.028 | − 0.268 | 1.179 | − 0.132 | 0.212 |
| BLMP | − 1.267 | − 0.370 | − 1.981 | 1.583 | 0.852 | 0.517 |
| BSFSP | − 0.903 | − 1.241 | 1.066 | − 0.796 | 0.794 | 0.381 |

*HLMP* ham lean meat percentage, *HSFSP* ham subcutaneous fat with skin percentage, *LLMP* loin lean meat percentage, *LSFSP* loin subcutaneous fat with skin percentage, *SLMP* shoulder lean meat percentage, *SSFSP* shoulder subcutaneous fat with skin percentage, *BLMP* belly lean meat percentage, *BSFSP* belly subcutaneous fat with skin percentage

**Table 8** The "goodness of fit" tests for the developed ANN model

| | $\chi^2$ | RMSE | MBE | MPE | $r^2$ | Residual analysis | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Skewness | Kurtosis | Average | SD |
| HLMP | 1.587 | 1.256 | − 0.117 | 1.395 | 0.928 | 0.112 | 0.999 | − 0.117 | 1.252 |
| HSFSP | 4.021 | 1.999 | 0.117 | 8.984 | 0.843 | − 0.126 | − 0.105 | 0.117 | 1.997 |
| LLMP | 4.799 | 2.183 | 0.023 | 2.922 | 0.861 | 0.184 | − 0.050 | 0.023 | 2.186 |
| LSFSP | 4.226 | 2.049 | − 0.075 | 8.120 | 0.885 | − 0.090 | 0.072 | − 0.075 | 2.050 |
| SLMP | 4.515 | 2.118 | 0.087 | 2.632 | 0.748 | − 0.187 | − 0.286 | 0.087 | 2.118 |
| SSFSP | 4.062 | 2.009 | 0.066 | 8.899 | 0.774 | 0.110 | 0.161 | 0.066 | 2.010 |
| BLMP | 9.865 | 3.130 | 0.236 | 4.638 | 0.806 | − 0.197 | − 0.527 | 0.236 | 3.125 |
| BSFSP | 14.708 | 3.822 | 0.117 | 13.247 | 0.616 | − 0.038 | 0.108 | 0.117 | 3.825 |

*HLMP* ham lean meat percentage, *HSFSP* ham subcutaneous fat with skin percentage, *LLMP* loin lean meat percentage, *LSFSP* loin subcutaneous fat with skin percentage, *SLMP* shoulder lean meat percentage, *SSFSP* shoulder subcutaneous fat with skin percentage, *BLMP* belly lean meat percentage, *BSFSP* belly subcutaneous fat with skin percentage, $\chi^2$ reduced Chi square, *RMSE* root mean square error, *MBE* mean bias error, *MPE* mean percentage error, $r^2$ coefficient of determination

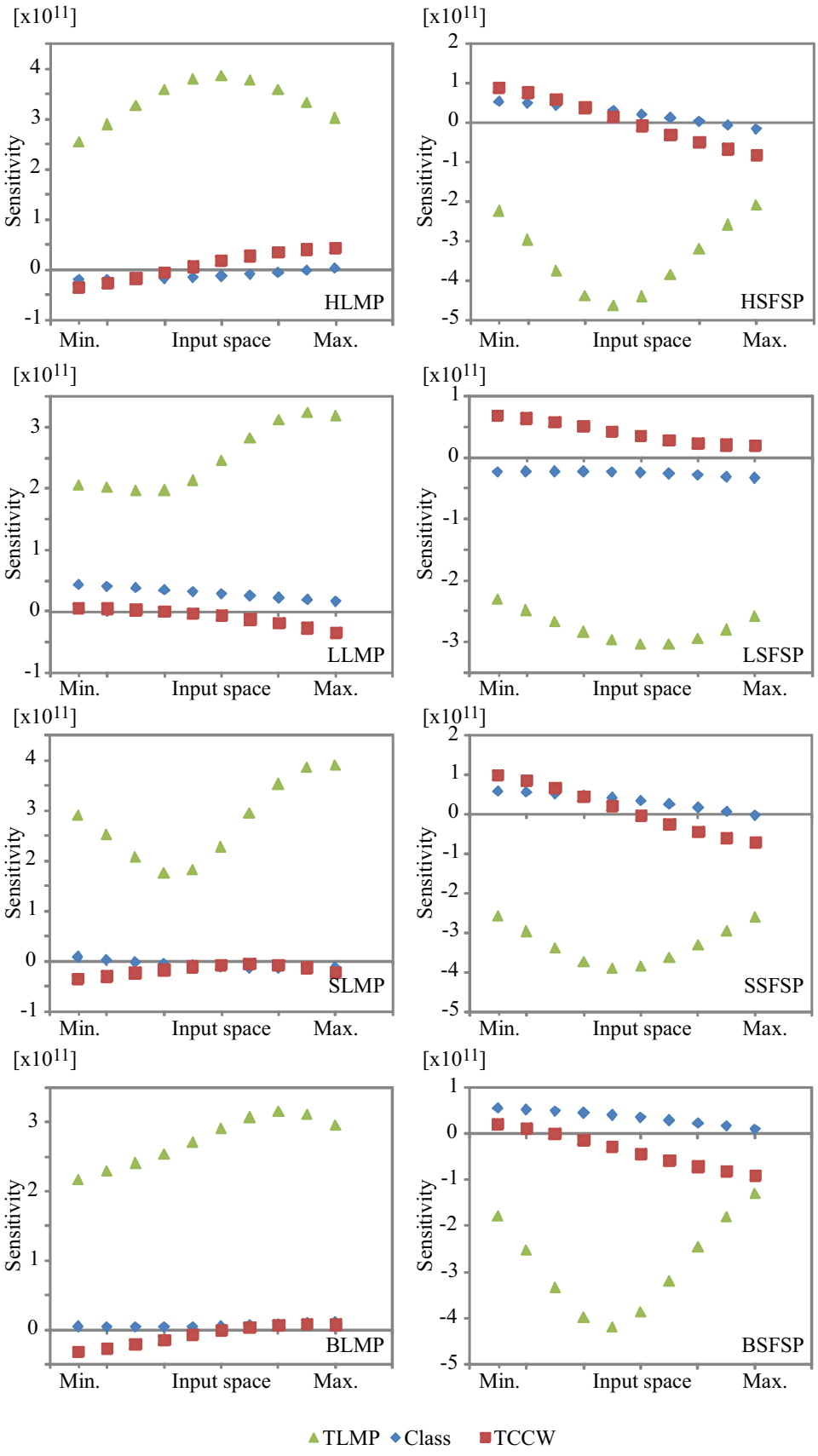


**Fig. 2** Sensitivity analysis—the influence of the input over the output variable

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## Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

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